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Improving Agricultural Water Use in the Texas High Plains: A Strategic Approach to Crop Switching and Optimal Land Allocation

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Improving Agricultural Water Use in the Texas High Plains: A Strategic Approach to Crop Switching and Optimal Land Allocation

[David Agboly, Shaihk Mafuz Rahman]

Agriculture in the Texas High Plains relies heavily on groundwater from the Ogallala Aquifer, making water scarcity a persistent challenge. This study develops a county-level optimization framework assessing whether reallocating irrigated land among corn, cotton, and sorghum can reduce groundwater use without undermining farm profitability. Using panel data from 2000–2022 for 41 counties, profit-maximizing (PMAX) and water-minimizing (WMIN) land allocations are compared under price uncertainty. Profit-oriented crop reallocation alone reduces regional irrigation water use from approximately 2.27 million acre-feet under baseline to about 1.78 million acre-feet under PMAX, a 21.90% reduction. An explicit water-minimization objective at a 5% expected-profit tolerance lowers water use only marginally further, to 1.77 million acre-feet (22.03% below baseline), because PMAX and WMIN select the same allocation in 38 of the 41 counties. Additional conservation beyond PMAX is concentrated in three counties (Donley, Roberts, and Randall) which together yield 2,903 acre-feet of extra savings at a total expected-profit sacrifice of about $272,041, implying a regional weighted Groundwater Abatement Price of approximately $93.70 per acre-foot. Most of the water-saving potential from crop switching is therefore already captured by profit-maximizing behavior, with remaining cost-effective conservation opportunities spatially concentrated rather than widespread across the region.

Key words: groundwater conservation, crop switching, land allocation, water–profit trade-off, Groundwater Abatement Price, Nested optimization

Introduction

Water scarcity has become one of the most binding constraints on agricultural production in semi-arid regions, where irrigation is essential for sustaining crop yields. Agriculture accounts for the largest share of freshwater withdrawals globally and remains the dominant user of groundwater in the United States (FAO, 2011; Schaible & Aillery, 2012). As climate variability increases

and population growth increases pressure on limited water supplies, the sustainability of irrigated agriculture has become an increasingly urgent concern.

In the United States, groundwater aquifers play a critical role in supporting crop production, particularly in regions where precipitation is insufficient to meet crop water requirements. The Ogallala Aquifer, which underlies much of the Great Plains, is among the most heavily exploited groundwater systems in the world. Decades of irrigation-driven withdrawals have resulted in substantial water-table declines across the Southern High Plains, threatening the long-term viability of irrigated agriculture in the region (Scanlon et al., 2012). Recent monitoring indicates that groundwater levels in many agricultural regions have reached historic lows, reinforcing the urgency of conservation-oriented management strategies (NASA, 2023).

Despite improvements in irrigation technology, groundwater withdrawals in many areas continue to exceed natural recharge. This suggests that efficiency gains alone may be insufficient to ensure sustainable water use. Crop production choices remain a central determinant of agricultural water demand. Water-intensive crops such as corn and irrigated cotton generate high economic returns but exert substantial pressure on groundwater resources, whereas more drought-tolerant crops such as sorghum require considerably less irrigation. Adjusting crop portfolios through strategic crop switching and land reallocation therefore presents a potentially effective pathway for reducing groundwater use while maintaining farm profitability.

However, producers face trade-offs between economic returns and water conservation, and these trade-offs vary substantially across locations due to differences in yields, prices, costs, and irrigation requirements. Understanding how these trade-offs differ spatially is critical for designing effective and economically feasible conservation policies.

This study develops a county-level optimization framework to evaluate the potential for strategic land reallocation and crop switching to improve water-use efficiency in the Texas High Plains. Using data from 2000–2022 on planted acreage, yields, irrigation intensity, prices, and production costs for corn, cotton, and sorghum, the model identifies both profit-maximizing (PMAX) and water-minimizing (WMIN) land allocation outcomes under explicit land and groundwater constraints. Uncertainty in crop prices is incorporated using kernel density estimation combined with Monte Carlo simulation, allowing expected utility to be evaluated under realistic market variability.

The contribution of this study is threefold. First, it provides a consistent county-level assessment of water–profit trade-offs across the Texas High Plains. Second, it quantifies the divergence between profit-maximizing and water-minimizing allocations, identifying counties where water conservation can be achieved at relatively low economic cost. Third, it introduces the Groundwater Abatement Price as a policy-relevant metric for evaluating the economic cost of groundwater con-

servation. Together, these results provide a practical decision-support framework for producers and policymakers seeking cost-effective groundwater conservation strategies in irrigation-dependent agricultural regions.

Literature Review

Agricultural production in water-limited regions is fundamentally constrained by the availability of irrigable land and groundwater resources (Varian, 2014; Mas-Colell, Whinston, & Green, 1995). Within a decision-theoretic framework, producers are modeled as rational economic agents who allocate land among alternative crops to maximize utility derived from farm-level outcomes subject to physical and economic constraints (Mas-Colell et al., 1995; Varian, 2014). When irrigation water is relatively abundant, optimal land allocation decisions are primarily driven by expected economic returns (Hardaker et al., 2015). As groundwater availability declines or extraction costs increase, optimal production choices must explicitly account for crop-specific water requirements and the opportunity cost of water use (Scanlon et al., 2012; Grafton et al., 2018).

Most policy and technical discourse on agricultural water conservation emphasize improvements in irrigation efficiency as a mechanism for reducing water use (Schaible & Aillery, 2012; Grafton et al., 2018). Economic theory, however, predicts that efficiency gains do not necessarily result in proportional reductions in total water withdrawals (Grafton et al., 2018). By lowering the effective marginal cost of irrigation, efficiency improvements may induce behavioral responses such as expansion of irrigated acreage or reallocation toward higher-value, water-intensive crops (Ward & Pulido-Velazquez, 2008). These rebound effects imply that efficiency-based interventions alone may be insufficient to achieve sustained reductions in groundwater extraction (Grafton et al., 2018).

Crop choice is therefore a primary determinant of agricultural water demand (Schaible & Aillery, 2012). Crops differ substantially in irrigation requirements, yield responses, and profitability, leading to heterogeneous impacts on groundwater use (Scanlon et al., 2012; Singh, 2022). Water-intensive crops such as corn and irrigated cotton often generate higher expected revenues but increase exposure to groundwater scarcity and pumping costs (Hardaker et al., 2015; Scanlon et al., 2012). In contrast, less water-intensive crops such as sorghum reduce irrigation demand but may involve lower or more variable returns (Singh, 2022; Chakraborti et al., 2023). Producers therefore face an inherent trade-off between economic performance and water conservation, particularly in regions where groundwater depletion poses long-run risks to agricultural viability (Hardaker et al., 2015; Scanlon et al., 2012).

A utility-based optimization framework provides a coherent method for evaluating these trade-offs

(Hardaker et al., 2015). In this framework, producers choose crop acreage allocations to maximize expected utility rather than expected profit alone, allowing risk preferences to influence land allocation decisions (Mas-Colell et al., 1995; Hardaker et al., 2015). When prices, yields, or water availability are uncertain, expected utility theory offers a behavioral foundation for incorporating risk into production choices (Hardaker et al., 2015). Risk-averse producers may prefer land allocation strategies that stabilize income or reduce dependence on water-intensive crops, even if those strategies do not strictly maximize expected profit under deterministic conditions (Hardaker et al., 2015).

The decision-theoretic framework also permits the evaluation of alternative optimization objectives within the same structural model (Varian, 2014; Habibi Davijani et al., 2016). A profit-oriented solution identifies the land allocation that maximizes expected economic returns subject to land and groundwater constraints (Habibi Davijani et al., 2016). A water conservation-oriented solution identifies the allocation that minimizes irrigation water use while maintaining economically feasible outcomes (Ward & Pulido-Velazquez, 2008; Liu et al., 2024). Comparing these solutions provides a transparent measure of the opportunity cost associated with groundwater conservation and clarifies the economic trade-offs implicit in water-saving strategies (Habibi Davijani et al., 2016; Qi, Sun, & Zhang, 2025).

Optimal land and water allocation decisions are inherently location specific due to heterogeneity in agronomic conditions, groundwater availability, production costs, and market environments (Scanlon et al., 2012; Liu et al., 2024). Spatially aggregated models may therefore obscure meaningful variation in water–profit trade-offs across production regions (Ward & Pulido-Velazquez, 2008; Qi, Sun, & Zhang, 2025). County-level analysis provides a more appropriate scale for capturing this heterogeneity and for identifying where groundwater conservation can be achieved at relatively low economic cost (Scanlon et al., 2012; Qi, Sun, & Zhang, 2025). By combining utility maximization, binding resource constraints, and spatially explicit data, the proposed framework offers a consistent and policy-relevant basis for evaluating how crop switching and land reallocation can contribute to sustainable groundwater management while preserving the economic viability of irrigated agriculture (Habibi Davijani et al., 2016; Liu et al., 2024).

Theoretical Model of Land and Water Allocation

The analysis considers the allocation of irrigated land among corn, cotton, and sorghum across counties in the Texas High Plains. Let $i = 1, \ldots, n$ index counties and $j = 1, \ldots, m$ index crops, where $n = 41$ and $m = 3$. The decision variable A_{ij} represents the irrigated acreage allocated to crop j in county i. At the regional level, the allocation problem can therefore be represented by

the set of county-crop acreage decisions

$$\mathbf{A} = \{A_{ij} : i = 1, \ldots, n;\ j = 1, \ldots, m\}. \tag{1}$$

The economic and water-use consequences of land allocation can be expressed generally across counties and crops as

$$\Pi(A, p) = \sum_{i=1}^{n} \sum_{j=1}^{m} \left(p_j Y_{ij} A_{ij} - p_{ij}^{w} W_{ij} A_{ij} - C_{ij} A_{ij}\right), \tag{2}$$

for economic returns, and

$$W(A) = \sum_{i=1}^{n} \sum_{j=1}^{m} W_{ij} A_{ij}, \tag{3}$$

for irrigation water use. These expressions summarize the regional economic and water-use implications of county-level crop allocations. The optimization itself is conducted separately for each county, allowing local differences in productivity, irrigation intensity, production costs, and water costs to determine the preferred allocation. County-level outcomes are subsequently aggregated to characterize regional economic and groundwater effects.

Construction of County-Level Production Parameters

The historical panel is used to construct the county-crop parameters required by the optimization model. Rather than relying exclusively on observations from 2022, representative production conditions are derived from recent valid observations. This approach reduces the influence of anomalous or unavailable observations in a single year while retaining recent differences in production conditions across counties.

For each county i and crop j, representative yield is defined as

$$Y_{ij} = \text{Median}\left\{Y_{ijt} : t \in T_{ij}^{Y}\right\}, \tag{4}$$

where Y_{ijt} denotes the observed yield of crop j in county i in year t, and T_{ij}^{Y} contains up to the five most recent valid yield observations. A county-specific value is used when at least three valid observations are available; otherwise, the corresponding regional median is used. This construction is consistent with the parameterization implemented in the model.

Irrigation intensity is first calculated from observed water use and irrigated acreage as

$$W_{ijt} = \frac{TW_{ijt}}{A_{ijt}}, \tag{5}$$

where TW_{ijt} is total irrigation water use and A_{ijt} is observed irrigated acreage. Representative irrigation intensity is then given by

$$W_{ij} = \text{Median}\left\{W_{ijt} : t \in T_{ij}^{W}\right\}, \tag{6}$$

where T_{ij}^{W} contains up to the five most recent valid observations. Thus, W_{ij} measures the representative acre-feet of irrigation water required per acre of crop j in county i.

Representative non-water production cost is similarly defined as

$$C_{ij} = \text{Median}\left\{C_{ijt} : t \in T_{ij}^{C}\right\}, \tag{7}$$

where C_{ijt} denotes production cost per acre and T_{ij}^{C} contains up to the five most recent valid observations.

Because the data contain separate water-price information for the three crops, the representative water-price parameter is defined as

$$p_{ij}^{w} = \text{Median}\left\{p_{ijt}^{w} : t \in T_{ij}^{p^w}\right\}, \tag{8}$$

where p_{ijt}^{w} denotes the observed water price associated with crop j in county i and year t. The computational model constructs this parameter from recent positive crop-specific observations, with a regional fallback when county-level information is insufficient.

The use of recent medians provides a stable representation of current production conditions while preserving county-level heterogeneity. Together, Y_{ij}, W_{ij}, C_{ij}, and p_{ij}^{w} characterize the agronomic and economic conditions under which each crop is evaluated.

Total irrigable land, A_i, defines the acreage available for allocation among the three crops in county i. The land base is held fixed across alternative strategies so that differences in model outcomes reflect changes in crop composition rather than changes in total irrigated acreage. Similarly, W_i represents the county's baseline irrigation-water limit and defines the water-use envelope within which alternative allocations are evaluated.

Profit Function

For each county i, net profit associated with a given crop allocation and realization of crop prices is defined as

$$\pi_i(\mathbf{A}_i, \mathbf{p}) = \sum_{j=1}^{m} \left(p_j Y_{ij} A_{ij} - p_{ij}^w W_{ij} A_{ij} - C_{ij} A_{ij} \right), \tag{9}$$

where p_j is the market price of crop j, Y_{ij} is yield per acre, A_{ij} is irrigated acreage allocated to crop j, W_{ij} is irrigation water use per acre, p_{ij}^w is the crop-specific water price, and C_{ij} denotes non-water production cost per acre. The first component, $p_j Y_{ij} A_{ij}$, represents crop revenue. The second, $p_{ij}^w W_{ij} A_{ij}$, represents irrigation water cost, while $C_{ij} A_{ij}$ captures non-water production cost. The profit function therefore accounts explicitly for differences in crop productivity, market returns, production costs, and irrigation requirements. Importantly, equation (9) contains a single summation because π_i represents profit for an individual county. The county index i is fixed when the optimization is solved, while profit is summed across the three crops allocated within that county.

Utility Maximization and Profit-Maximizing Allocation (PMAX)

Producers are modeled as utility maximizers under uncertain crop prices. Preferences are represented by a logarithmic utility function,

$$U(\pi_i) = \ln(\pi_i), \tag{10}$$

which corresponds to a constant relative risk aversion (CRRA) coefficient of one and captures diminishing marginal utility of profit. Conceptually, the producer's land-allocation problem under price uncertainty is

$$\max_{A_i} E_p \left[U \left(\pi_i(A_i, p) \right) \right]. \tag{11}$$

Utility formulation provides the theoretical basis for producer decision-making under uncertainty. In the empirical analysis, expected net profit is used as the operational economic criterion for identifying the profit-maximizing allocation (PMAX). This provides a direct monetary measure of economic performance and facilitates comparison of the economic consequences of alternative groundwater-conservation strategies.

Accordingly, PMAX is defined as

$$A_i^{PMAX} \in \arg\max_{A_i} E_p \left[\pi_i(A_i, p) \right] \tag{12}$$

subject to

$$\sum_{j=1}^{m} A_{ij} = A_i, \tag{13}$$

$$\sum_{j=1}^{m} W_{ij} A_{ij} \leq W_i, \tag{14}$$

and

$$A_{ij} \geq 0, \quad j = 1, \ldots, m. \tag{15}$$

Equation (13) requires total acreage allocated among the three crops to equal the county's available irrigated land. Equation (14) restricts total irrigation water use to the county's baseline irrigation-water limit, while Equation (15) imposes non-negativity on crop acreage. These constraints define the feasible set of land-allocation strategies. By holding land and water-use constant, changes in expected profit and irrigation water use can be attributed to changes in crop composition.

The corresponding maximum expected profit is given in equation (16):

$$\pi_i^{\max} = E_p \left[\pi_i \left(A_i^{PMAX}, p \right) \right]. \tag{16}$$

PMAX therefore identifies the feasible crop allocation that generates the highest expected net return in county i.

Water-Minimizing Allocation (WMIN)

The water-minimizing allocation identifies the crop allocation that uses the least irrigation water while maintaining expected profit within a specified tolerance of the PMAX benchmark. For county i, the WMIN problem is

$$A_i^{WMIN}(\varepsilon) \in \arg\min_{A_i} \sum_{j=1}^{m} W_{ij} A_{ij} \tag{17}$$

subject to the same land, water, and non-negativity constraints as PMAX (equations (13)–(15)), together with an additional economic constraint that limits the allowable reduction in expected profit relative to PMAX:

$$E_p \left[\pi_i(A_i, p) \right] \geq \pi_i^{\max} - \varepsilon \left| \pi_i^{\max} \right|. \tag{18}$$

The parameter ε represents the maximum allowable reduction in expected profit relative to the magnitude of the PMAX benchmark. The analysis considers

$$\varepsilon \in \{0,\ 0.05,\ 0.10\}, \tag{19}$$

with $\varepsilon = 0.05$ serving as the primary conservation scenario.

At $\varepsilon = 0$, the model searches for the least water-intensive allocation that maintains the PMAX expected-profit level. At $\varepsilon = 0.05$, expected profit may decline by up to 5% of the absolute value of the PMAX benchmark, while $\varepsilon = 0.10$ permits a reduction of up to 10%. Increasing ε therefore expands the set of economically admissible allocations and allows the model to determine whether additional groundwater savings can be achieved by accepting a larger economic sacrifice. The absolute-value term, $|\pi_i^{\max}|$, ensures that the allowable profit reduction is defined relative to the magnitude of the PMAX benchmark regardless of whether expected profit is positive or negative. Thus, positive expected profit is not imposed as an additional requirement for WMIN feasibility.

Together, PMAX and WMIN characterize the economic trade-off between profitability and groundwater conservation. PMAX establishes the allocation preferred based on expected economic returns, while WMIN determines how much additional irrigation water can be conserved when a limited reduction in expected profit is permitted. The comparison therefore identifies counties where crop reallocation can reduce groundwater use with little economic sacrifice and counties where additional conservation entails a larger opportunity cost.

Candidate Land-Allocation Strategies

The optimization evaluates a discrete set of 66 alternative land-allocation strategies for each county. Each strategy specifies the proportion of the county's available irrigated acreage allocated among corn, cotton, and sorghum. Let $s = 1, \ldots, S$ index the candidate strategies, where $S = 66$. The crop shares associated with strategy s are denoted by

$$\boldsymbol{\alpha}_s = (\alpha_{s1}, \alpha_{s2}, \ldots, \alpha_{sm}), \tag{20}$$

where α_{sj} represents the proportion of irrigated land assigned to crop j under strategy s. The shares satisfy

$$\sum_{j=1}^{m} \alpha_{sj} = 1, \quad 0 \leq \alpha_{sj} \leq 1. \tag{21}$$

For county i, the acreage allocated to crop j under strategy s is therefore

$$A_{ijs} = \alpha_{sj} A_i, \tag{22}$$

where A_i is the county's fixed irrigated land base. Consequently,

$$\sum_{j=1}^{m} A_{ijs} = A_i. \tag{23}$$

Each candidate strategy is evaluated using the county-specific production parameters defined above. Irrigation water use associated with strategy s is calculated as

$$W_{is} = \sum_{j=1}^{m} W_{ij} A_{ijs}. \tag{24}$$

A strategy is considered physically feasible only when its total irrigation requirement does not exceed the county's baseline irrigation-water limit:

$$W_{is} \leq W_i. \tag{25}$$

Expected profit for each feasible strategy is evaluated using the stochastic price framework described in the following subsection. PMAX selects the feasible strategy with the highest expected profit, whereas WMIN selects the feasible strategy with the lowest irrigation water requirement while satisfying the specified expected-profit tolerance.

The use of a common set of allocation strategies across counties provides a consistent basis for comparison while allowing the economic and water-use consequences of each strategy to vary according to local production conditions. Because total irrigated acreage remains fixed, changes in profit and groundwater use reflect crop substitution within the existing land base, rather than changes in the scale of irrigated production.

This discrete strategy framework is also important for interpreting the results. The analysis does not assume that acreage can be adjusted continuously to any possible crop combination. Instead, it compares a defined set of alternative crop mixes, allowing the model to identify economically and hydrologically preferable reallocations from the available strategy set.

Price Uncertainty and Monte Carlo Simulation

Crop prices are treated as stochastic because the profitability of alternative crop allocations depends on uncertain market conditions. Price uncertainty is incorporated using historical annual prices for corn, cotton, and sorghum over the most recent ten-year period, 2013–2022. The same simulated price environment is applied to all candidate strategies, ensuring that differences in expected profitability arise from differences in crop allocation rather than differences in the price draws used to evaluate the strategies.

For crop j, the marginal price distribution is represented using a Gaussian kernel density estimator,

$$\hat{f}_j(p) = \frac{1}{Th_j} \sum_{t=1}^{T} K\left(\frac{p - p_{jt}}{h_j}\right), \tag{26}$$

where p_{jt} is the observed price of crop j in year t, T is the number of historical price observations, h_j is the crop-specific bandwidth, and $K(\cdot)$ denotes the Gaussian kernel.

Because crop prices may move together in response to common market conditions, the simulation preserves the historical co-movement among corn, cotton, and sorghum prices. A common historical year is sampled for the three crops, after which crop-specific Gaussian kernel noise is added around the observed prices. This procedure maintains the dependence contained in the historical price combinations while allowing continuous variation around the observed values.

A total of

$$R = 10{,}000 \tag{27}$$

Monte Carlo price realizations are generated. For each county i, strategy s, and simulation r, simulated profit is

$$\pi_{is}^{(r)} = \sum_{j=1}^{m} \left(p_j^{(r)} Y_{ij} A_{ijs} - p_{ij}^{w} W_{ij} A_{ijs} - C_{ij} A_{ijs}\right), \tag{28}$$

where $p_j^{(r)}$ denotes the simulated price of crop j in realization r.

Expected profit for strategy s is approximated by the Monte Carlo mean:

$$E_{\mathbf{p}}[\pi_{is}] \approx \frac{1}{R} \sum_{r=1}^{R} \pi_{is}^{(r)}. \tag{29}$$

The simulated distribution also provides information on the variability of returns across price realizations. However, expected profit remains the principal economic criterion used to identify PMAX and evaluate the profit constraint imposed under WMIN.

Using common price draws across strategies ensures that candidate allocations within a county are evaluated under identical simulated market conditions. This improves comparability among strategies and isolates the effect of changing crop composition on expected economic returns.

Two diagnostic checks support the simulation design. First, Appendix Table A2 compares the historical (2013–2022) and simulated correlation structure among sorghum, cotton, and corn prices: the simulated draws preserve the sign and approximate magnitude of the historical co-movement, though correlations attenuate somewhat toward independence as crop-specific kernel noise is added around the sampled historical year. Second, Appendix Table A3 reports the simulated price means at 1,000, 2,500, 5,000, 7,500, and 10,000 draws; the means stabilize well before the full 10,000-draw specification, indicating that the simulation has converged and that the reported expected-profit estimates are not sensitive to further increases in the number of Monte Carlo draws.

Groundwater Abatement Price

The economic cost of obtaining additional groundwater conservation is measured by comparing PMAX with WMIN. For county i, the additional water saving achieved by moving from PMAX to WMIN is

$$\Delta W_i = W_i^{PMAX} - W_i^{WMIN}, \tag{30}$$

where W_i^{PMAX} and W_i^{WMIN} denote irrigation water use under the two allocations.

The corresponding expected-profit sacrifice is

$$\Delta \pi_i = E\left[\pi_i^{PMAX}\right] - E\left[\pi_i^{WMIN}\right]. \tag{31}$$

For counties in which WMIN produces positive additional water savings, the groundwater abatement price (GAP) is defined as

$$GAP_i = \frac{E\left[\pi_i^{PMAX}\right] - E\left[\pi_i^{WMIN}\right]}{W_i^{PMAX} - W_i^{WMIN}} \tag{32}$$

and is expressed in dollars of expected profit forgone per acre-foot of additional groundwater conserved.

The GAP provides a county-specific measure of the economic opportunity cost of additional groundwater conservation through crop reallocation. A relatively low GAP indicates that additional water savings can be obtained with a small reduction in expected profit, whereas a high GAP indicates that further conservation through crop switching carries a larger economic sacrifice.

Data

The analysis focuses on irrigated crop production in the Texas High Plains, where agricultural production relies heavily on groundwater from the Ogallala Aquifer. The region provides an important setting for examining the economic consequences of groundwater conservation because crop profitability and irrigation requirements vary substantially across space and across cropping systems. Corn, cotton, and sorghum constitute the crop choice set considered in the analysis because they dominate irrigated acreage in the region. Differences in their yield potential, production costs, market returns, and irrigation intensity create an economic margin through which producers may conserve groundwater by altering crop composition.

The county is used as the spatial decision unit. This scale allows the analysis to preserve heterogeneity in production conditions rather than imposing a single representative technology across the Texas High Plains. Accordingly, the optimization framework does not seek a uniform regional crop allocation. Instead, each county is assigned its own production parameters and resource constraints, and the economically preferred conservation strategy is determined independently for that county. The resulting framework therefore permits the profitability of groundwater conservation to vary spatially with local agricultural conditions.

The central economic question is whether crop reallocation alone can generate meaningful groundwater savings without requiring large reductions in expected agricultural profit. This question is evaluated by comparing two allocation benchmarks: a profit-maximizing allocation (PMAX) and a water-minimizing allocation (WMIN) subject to an allowable profit sacrifice. The difference between these solutions identifies both the physical potential for additional groundwater conservation and its associated economic opportunity cost.

The empirical analysis uses county-level data for 41 counties in the Texas High Plains over the period 2000–2022 (943 county-year observations). The dataset contains annual observations on irrigated acreage, crop yields, irrigation water use, output prices, and production costs for corn, cotton, and sorghum. Irrigated acreage and yield data are obtained from the USDA National Agricultural Statistics Service (NASS), while production costs are drawn from crop enterprise budgets. Historical crop prices are used to characterize market uncertainty, and irrigation water-use data provide information on crop- and county-specific groundwater requirements. Missing and nonpositive yield observations are common in a panel of this length — Appendix Table A1 reports 359, 296, and 541 zero, nonpositive, or missing yield observations for sorghum, cotton, and corn, respectively, out of 943 county-year records — which motivates the median-based construction of representative production parameters described below rather than reliance on any single year.

The panel structure is particularly useful for the analysis because agricultural production conditions vary across both space and time. Counties differ in crop productivity, cropping patterns, and irrigation requirements, while annual market and production conditions also fluctuate. These differences imply that the potential for groundwater conservation through crop switching is unlikely to be uniform across the study region. The county-level data therefore provides the spatial detail necessary to evaluate alternative land allocations under heterogeneous production conditions. Irrigation water use is measured in acre-feet and varies substantially across crops and counties. Crop-specific water use, together with observed irrigated acreage, provides the baseline distribution of irrigation demand across the Texas High Plains. This baseline characterizes the existing crop-water relationship and provides an empirical reference for evaluating the water implications of alternative crop allocations.

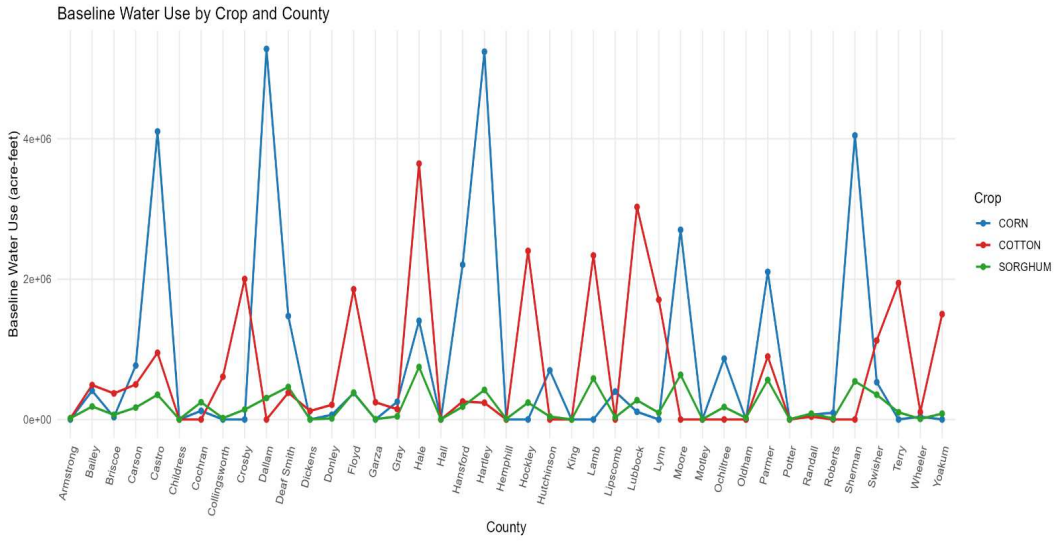


Figure 1: Baseline irrigation water usage by crops and counties in the Texas High Plains.

Figure 1 illustrates substantial variation in baseline irrigation water use across crops and counties in the Texas High Plains. Aggregated across the 41 counties over the study period, irrigation water use totals approximately 36.15 million acre-feet for corn, 30.74 million acre-feet for cotton, and 7.60 million acre-feet for sorghum. Corn therefore accounts for the largest volume of irrigation water use, followed by cotton, while sorghum represents a considerably smaller share of total irrigation demand. These differences highlight the potential role of crop switching in groundwater conservation. Because crops differ in their irrigation requirements, reallocating acreage from relatively water-intensive crops to crops with lower water requirements can reduce groundwater use. However, the potential savings depend not only on the crop being replaced, but also on county-specific irrigation intensity and the amount of acreage available for reallocation. As a result, similar changes in crop composition may produce different water savings across counties.

Figure 1 also shows that irrigation water use is unevenly distributed across the Texas High Plains. This spatial heterogeneity is important because counties with different cropping patterns and irrigation requirements are unlikely to face the same opportunities or economic costs of groundwater conservation. A county-level approach therefore allows the analysis to account for these differences rather than relying on regional averages that may conceal important variation in production and water-use conditions. The baseline distribution provides an empirical reference for evaluating alternative land-allocation strategies. The optimization framework builds on these observed differences to examine whether reallocating existing irrigated acreage among corn, cotton, and sorghum can reduce groundwater use while preserving economically viable production. In this way, the analysis links the observed spatial pattern of irrigation demand directly to the economic trade-offs associated with crop switching.

Empirical Analysis and Simulation Results

The empirical implementation follows a nested county-strategy-simulation procedure. Representative production parameters are first constructed for each county-crop combination as described above. The 66 candidate land-allocation strategies are then applied to each county's fixed irrigated land base, and strategies that violate the baseline irrigation-water constraint are excluded. Each feasible strategy is evaluated under the same 10,000 simulated crop-price realizations. Expected profit and irrigation water use are calculated for every county-strategy combination. PMAX is identified as the feasible strategy that generates the highest expected profit. Using the resulting $\pi_i^{\max}$ as the economic benchmark, WMIN is then identified separately for each value of $\varepsilon \in \{0,\ 0.05,\ 0.10\}$. For each tolerance level, WMIN selects the feasible strategy with the lowest irrigation water use while satisfying the corresponding expected-profit constraint. Model consistency is assessed by verifying that selected strategies satisfy the land and water constraints and that WMIN satisfies its specified profit tolerance. PMAX expected profit must be at least as large as WMIN expected profit, while WMIN irrigation water use cannot exceed the corresponding PMAX level. The $\varepsilon = 0$, 0.05, and 0.10 scenarios also provide a sensitivity assessment of how the conservation outcome changes as progressively larger reductions in expected profit are permitted. Finally, county-level PMAX and WMIN outcomes are aggregated to evaluate regional changes in irrigation water use and expected profit. The county-level comparison identifies where crop switching can provide additional groundwater conservation at relatively low economic cost and where the profit-water trade-off is more pronounced.

This subsection focuses on results obtained from the stochastic optimization framework, which incorporates crop price uncertainty through kernel density estimation and Monte Carlo simulation.

By explicitly accounting for price risk and producer risk preferences, the stochastic framework provides a more realistic representation of land allocation decisions than deterministic reallocations and allows evaluation of how uncertainty shapes optimal crop choices, profitability, and groundwater use.

Strategy Winners and the Divergence across Land Reallocation Strategies

Table 1 shows that Strategy_57 (100% sorghum) dominates the allocation outcomes, ranking first under both the profit-maximizing and water-minimizing objectives. Strategy_57 is selected in 35 of the 41 counties under PMAX and 36 counties under WMIN, indicating that sorghum provides a strong combination of expected economic returns and relatively low irrigation requirements under the modeled conditions.

The remaining strategies are selected less frequently. Strategy_61 (80% sorghum and 20% corn) emerges under WMIN in two counties, reflecting the additional flexibility created by the 5% expected-profit tolerance. Overall, PMAX and WMIN select different strategies in only three counties, showing that the two objectives are closely aligned across most of the Texas High Plains. Where divergence occurs, the WMIN allocation shifts acreage toward sorghum and away from corn, generating additional groundwater savings while keeping the reduction in expected profit within the specified tolerance.

Table 1: Strategy Performance Ranking across the Texas High Plains

Strategy	**Profit max**	**Water min**	**Mean water saving (%)**	**Strategy type**
Strategy_57	35	36	20.46%	Sorghum (100%)
Strategy_1	1	1	9.20%	Cotton (100%)
Strategy_61	0	2	15.18%	Sorghum (80%), Corn (20%)
Strategy_38	1	1	−17.33%	Sorghum (80%), Cotton (20%)
Strategy_8	1	1	−8.12%	Sorghum (30%), Cotton (70%)
Strategy_63	1	0	7.64%	Sorghum (70%), Corn (30%)
Strategy_65	1	0	5.39%	Sorghum (60%), Corn (40%)
Strategy_66	1	0	4.91%	Sorghum (50%), Corn (50%)

Note: Profit max reports the number of counties in which each strategy is selected under PMAX, while Water min reports selections under WMIN at the 5% expected-profit tolerance. Mean water saving is measured relative to the baseline irrigation allocation for the counties in which each strategy is selected. Negative values indicate that the strategy increases irrigation water use relative to baseline.

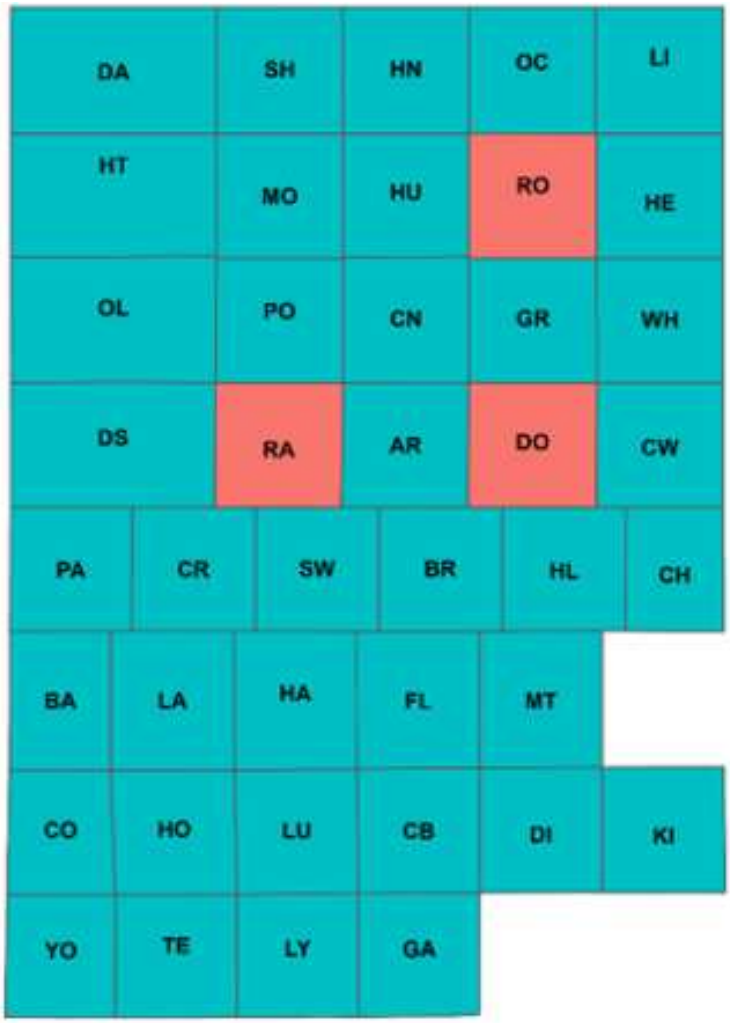


Figure 2: Divergence between water-minimizing and profit-maximizing strategies across the Texas High Plains.

Regional Water Savings under Land Reallocation Strategies

Table 2 shows that both optimized land-allocation scenarios reduce regional irrigation water use relative to the baseline. Under PMAX, total water use declines from 2.273 million AF to 1.775 million AF, representing a saving of approximately 497.78 thousand AF, or 21.90% of baseline water use. This result indicates that substantial groundwater conservation can be achieved through profit-oriented crop reallocation without explicitly minimizing water use. At the 5% expected-profit tolerance, WMIN reduces total irrigation water use further to 1.772 million AF, corresponding to total savings of 500.69 thousand AF (22.03%) relative to baseline. However, the additional saving from moving from PMAX to WMIN is only about 2.90 thousand AF. The relatively small difference between the two optimized scenarios suggests that most of the water-saving potential identified by the model is already captured by the profit-maximizing allocation. Additional conservation through crop reallocation is therefore limited when expected profit is required to remain close to the PMAX benchmark.

Table 2 also reports regional expected profit under each scenario. Moving from the baseline allocation to PMAX raises expected profit from \$275.50 million to \$1,081.74 million—an increase of \$806.24 million, or nearly a fourfold (3.93×) increase. This gain reflects both higher expected revenue and substantially lower production costs under the optimized, largely sorghum-dominant allocations relative to the historical baseline crop mix, and it is materially larger than the profit consequences of the PMAX-to-WMIN water-conservation trade-off discussed below. Expected profit under WMIN at the 5% tolerance (\$1,081.47 million) is, by construction, within 5% of the PMAX benchmark.

Table 2: Regional Aggregation of Water Savings and Expected Profit under Alternative Land-Allocation Scenarios

Scenario	**Total water usage (1,000 AF)**	**Baseline share (%)**	**Water savings (1,000 AF)**	**Percentage water savings (%)**	**Expected profit (\$ million)**
Baseline	2,273.17	100.00	0.00	0.00	275.50
Profit-maximizing (PMAX)	1,775.38	78.10	497.78	21.90	1,081.74
Water-minimizing (WMIN, $\varepsilon = 5\%$)	1,772.48	77.98	500.69	22.03	1,081.47

Note: Water savings represent the reduction in total irrigation water use relative to the baseline allocation. Baseline share is the percentage of baseline irrigation water use remaining under each scenario. WMIN is evaluated at the 5% expected-profit tolerance. AF = acre-feet. Values are rounded to two decimal places.

Sensitivity to the Expected-Profit Tolerance

The WMIN objective is defined for $\varepsilon \in \{0, 0.05, 0.10\}$ (equation (19)). Table 3 reports the regional outcome at each tolerance level. At $\varepsilon = 0$, WMIN reproduces the PMAX allocation exactly—no

county selects a different strategy, so there is no additional water saving or profit sacrifice relative to PMAX. This confirms that the profit-maximizing allocation is itself feasible under the strict zero-tolerance conservation objective.

Relaxing the tolerance to $\varepsilon = 0.10$ produces a markedly larger response than the $\varepsilon = 0.05$ case discussed above. Regional water use falls further to approximately 1.760 million AF, an additional 15.15 thousand AF beyond PMAX (roughly five times the saving obtained at the 5% tolerance), at a total expected-profit sacrifice of approximately $41.20 million. The implied regional weighted GAP at $\varepsilon = 0.10$ is therefore approximately $2,720 per acre-foot—about 29 times higher than the $93.70 per acre-foot weighted GAP at $\varepsilon = 0.05$. Appendix Table A4 shows that this larger response is driven by seven counties switching to Strategy_47 (90% sorghum, 10% cotton) and one county switching to Strategy_40, in place of the strategies selected at lower tolerances. Together, these results indicate sharply diminishing returns to relaxing the profit constraint: the first 5 percentage points of allowable profit sacrifice buy relatively cheap conservation in three counties, while the next 5 points draw in additional counties at a substantially higher marginal cost per acre-foot.

Table 3: Sensitivity of Regional Water Savings and Expected Profit to the WMIN Profit Tolerance

Tolerance (ε)	**Total water (1,000 AF)**	**Additional water saved vs. PMAX (AF)**	**Expected profit ($ million)**	**Profit sacrifice vs. PMAX ($ million)**
0.00	1,775.38	0.00	1,081.74	0.00
0.05	1,772.48	2,903.19	1,081.47	0.27
0.10	1,760.24	15,148.87	1,040.54	41.20

Note: Additional water saved and profit sacrifice are measured relative to the PMAX allocation. $\varepsilon = 0$ reproduces the PMAX regional outcome exactly. AF = acre-feet.

The crop-specific composition of irrigation water use also shifts with the conservation objective. Table 4 decomposes total regional water use by crop under each scenario. Corn is the crop most affected by optimization: its water use falls from 1,149.94 thousand AF under the baseline to just 15.20 thousand AF under PMAX, and to 5.87 and 0.02 thousand AF under WMIN at the 5% and 10% tolerances, respectively—corn is effectively phased out of the optimized allocations. Sorghum water use rises correspondingly, from 236.62 thousand AF at baseline to 1,699.69 thousand AF under PMAX, consistent with Strategy_57 (100% sorghum) dominating the county-level rankings in Table 1. Cotton water use falls from 886.60 thousand AF at baseline to roughly 60 thousand AF under PMAX and the 5% WMIN tolerance, but rises again to 118.31 thousand AF at the 10% tolerance as counties adopt the mixed sorghum–cotton Strategy_47 identified above.

Table 4: Regional Crop-Specific Irrigation Water Use by Scenario

Scenario	Sorghum (1,000 AF)	Cotton (1,000 AF)	Corn (1,000 AF)	Total (1,000 AF)
Baseline	236.62	886.60	1,149.94	2,273.17
PMAX	1,699.69	60.49	15.20	1,775.38
WMIN ($\varepsilon = 5\%$)	1,706.12	60.49	5.87	1,772.48
WMIN ($\varepsilon = 10\%$)	1,641.92	118.31	0.02	1,760.24

Note: Values are expressed in thousand acre-feet and may not sum exactly due to rounding.

County-Level Percentage Reduction in Irrigation Water Use from Profit-Maximizing to Water-Minimizing Allocations

Figure 3 highlights the spatial distribution of additional groundwater savings obtained when the model moves from the profit-maximizing (PMAX) allocation to the water-minimizing (WMIN) allocation at the 5% expected-profit tolerance. The results show that water savings are highly concentrated, with only three counties recording positive reductions in irrigation water use. Roberts County records the highest percentage reduction at 14.47%, followed by Randall County at 10.71% and Donley County at 6.67%. On the map, these counties are distinguished from the remaining counties by their higher percentage reductions in water use.

Although Roberts records the largest percentage reduction, it does not generate the largest absolute water saving. As shown in Table 5, Donley County contributes the largest absolute saving at 1,145.83 AF, despite having the lowest percentage reduction among the three counties. Roberts follows with 1,014.36 AF, while Randall records 743.00 AF. This difference illustrates the importance of considering both percentage and absolute water savings when evaluating county-level conservation outcomes, since a larger proportional reduction does not necessarily translate into the largest volume of groundwater conserved. These observations are consistent with the results reported in Table 5, which show that only 3 of the 41 counties experience additional water savings when the objective shifts from profit maximization to water minimization. Together, Donley, Roberts, and Randall account for 2,903.19 AF of additional groundwater conservation. In these counties, different land-allocation strategies are selected under PMAX and WMIN, resulting in lower irrigation water requirements under the WMIN objective. In contrast, the remaining 38 counties exhibit no additional reduction in irrigation water use, as indicated by the dark-blue areas in Figure 3. For these counties, PMAX and WMIN select the same land-allocation strategy at the 5% expected-profit tolerance, resulting in identical water-use levels under the two objectives. Therefore, the county-level results show that the opportunity for additional groundwater conservation beyond the PMAX allocation is concentrated in Roberts, Randall, and Donley, rather than being broadly distributed across the Texas High Plains.

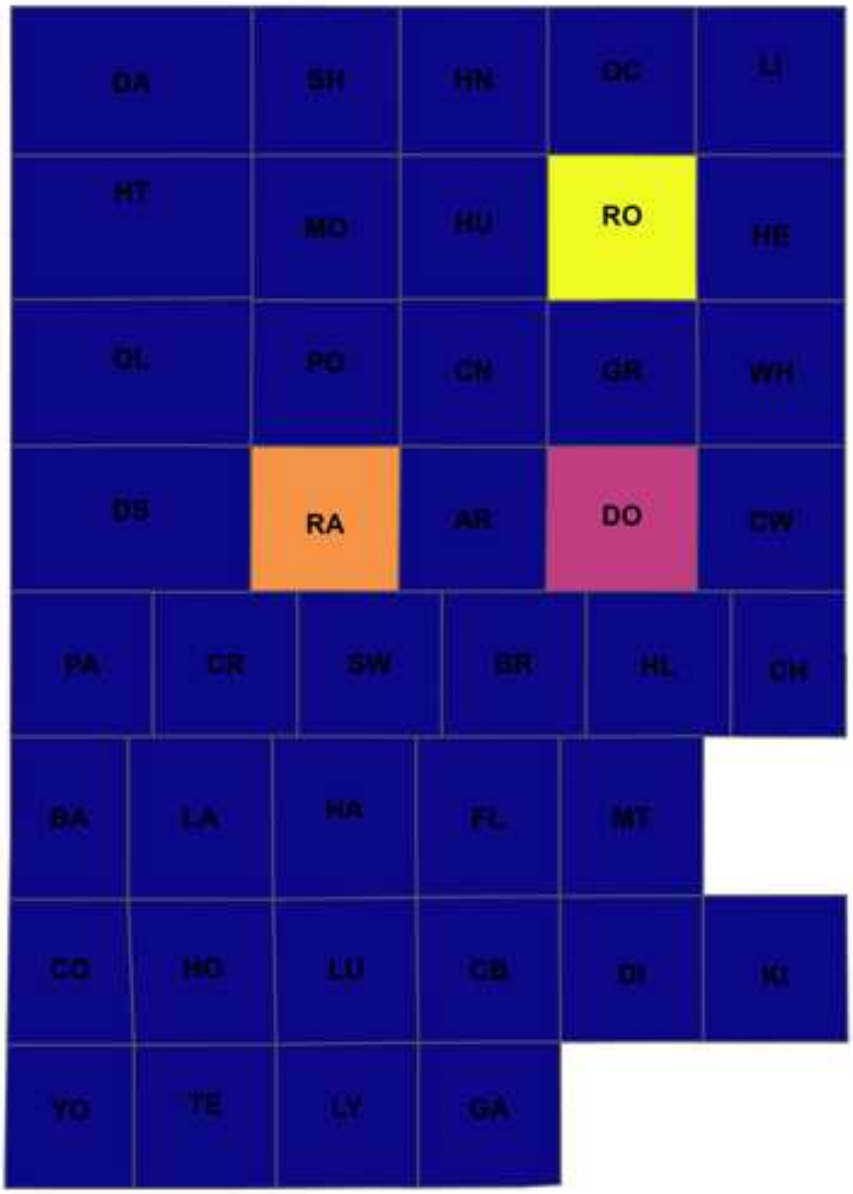


Figure 3: Percentage of water saved by counties across the Texas High Plains.

Table 5: County-Level Water Savings under PMAX–WMIN Land Reallocation at the 5% Expected-Profit Tolerance

County	Water saved (AF)	Water saved (%)
Donley	1,145.83	6.67
Randall	743.00	10.71
Roberts	1,014.36	14.47

Note: Only counties with positive additional water savings from PMAX to WMIN are reported. Water saved is calculated as the difference between irrigation water use under the PMAX and WMIN allocations. WMIN is evaluated at the 5% expected-profit tolerance. AF = acre-feet.

Expected Profit Trade-offs Associated with Groundwater Conservation

Table 6 presents the expected profit trade-offs associated with moving from the profit-maximizing allocation to the water-minimizing allocation. Consistent with the county-level water-saving results, positive profit sacrifices occur in only three counties. Donley records the largest expected-profit sacrifice at approximately $128,780, followed by Roberts at $88,476 and Randall at $54,785. Together, the three counties account for a total expected-profit sacrifice of approximately $272,041. The remaining 38 counties experience no expected-profit sacrifice because PMAX and WMIN select the same land-allocation strategy at the 5% tolerance. Consequently, there is no change in either expected profit or irrigation water use between the two objectives in these counties. The economic trade-off associated with obtaining additional groundwater savings is therefore concentrated in the same three counties identified in the water-saving analysis. When considered together with Table 5, the results also show that the magnitude of the profit sacrifice does not correspond directly to the percentage of water saved. Donley has the largest profit sacrifice and the largest absolute water saving (1,145.83 AF), whereas Roberts records the highest percentage reduction in water use (14.47%). Randall has the smallest profit sacrifice at $54,784.79 and saves 743.00 AF. These differences indicate that the economic cost of obtaining an additional acre-foot of groundwater conservation varies across the three counties. This variation is captured more directly by the groundwater abatement price (GAP), which is discussed next.

County-Level Analysis of the Groundwater Abatement Price (GAP)

Table 7 reports county-level Groundwater Abatement Prices (GAPs), measured as the expected-profit sacrifice per acre-foot of additional groundwater conserved when moving from the profit-maximizing (PMAX) allocation to the water-minimizing (WMIN) allocation. At the 5% expected-

Table 6: Expected-Profit Trade-offs from PMAX to WMIN in the Texas High Plains

County	**Expected Profit Sacrifice ($ Million)**
Donley	0.129
Randall	0.055
Roberts	0.088
Total	**0.272**

Note: Expected-profit sacrifice is calculated as the difference between expected profit under the PMAX and WMIN allocations at the 5% expected-profit tolerance. The remaining 38 counties are not reported because PMAX and WMIN selected the same land-allocation strategy, resulting in no expected-profit sacrifice.

profit tolerance, positive GAP values are observed only in Randall, Roberts, and Donley counties, reflecting the limited number of counties where the PMAX and WMIN strategies diverge. Across these counties, the regional weighted GAP is approximately $93.70 per acre-foot (mean county GAP $91.12/AF; median $87.22/AF), providing a measure of the economic cost of achieving additional groundwater conservation beyond the PMAX allocation. The GAP values vary across the three counties. Randall records the lowest abatement price at $73.73/AF, followed by Roberts at $87.22/AF, indicating that additional groundwater savings can be achieved in these counties at relatively lower expected-profit sacrifices per acre-foot. Randall conserves approximately 743 AF, while Roberts conserves 1,014 AF when moving from PMAX to WMIN. Donley records the highest GAP at $112.39/AF, with approximately 1,146 AF of additional groundwater savings. Although Donley provides the largest absolute water saving, achieving this reduction involves a higher expected-profit sacrifice per acre-foot than in Randall and Roberts. As discussed above, the weighted GAP rises sharply to approximately $2,720 per acre-foot once the profit tolerance is relaxed to $\varepsilon = 0.10$ (Table 3), underscoring that the low-cost conservation identified here is exhausted quickly as the region moves beyond the first three divergent counties.

The remaining 38 counties do not have a defined GAP because PMAX and WMIN select the same land-allocation strategy at the 5% expected-profit tolerance. As a result, these counties generate no additional water savings and incur no corresponding expected-profit sacrifice when moving between the two objectives. Overall, the GAP results show that both the opportunity and economic cost of additional groundwater conservation beyond PMAX are concentrated in a small number of counties. The differences among Randall, Roberts, and Donley further indicate that the cost of conserving an additional acre-foot of groundwater varies spatially, providing a basis for considering county-specific differences when evaluating groundwater conservation strategies.

Table 7: Groundwater Abatement Price from PMAX to WMIN at the 5% Expected-Profit Tolerance

County	Water Saved (AF)	Expected-Profit Sacrifice ($)	GAP ($/AF)
Donley	1,145.83	128,779.89	112.39
Roberts	1,014.36	88,476.05	87.22
Randall	743.00	54,784.79	73.73
Regional Average	**2,903.19**	**272,040.73**	**93.70**

Note: GAP denotes the groundwater abatement price and is calculated as the expected-profit sacrifice associated with moving from PMAX to WMIN divided by the additional groundwater conserved. The regional GAP of $93.70/AF is a water-savings-weighted measure calculated from the total expected-profit sacrifice divided by total additional water saved. The remaining 38 counties have no additional PMAX-to-WMIN water savings and therefore do not have a defined GAP. AF = acre-feet.

Conclusion and Policy Implications

Groundwater depletion remains an important constraint to irrigated agricultural production in the Texas High Plains. This study evaluates whether reallocating land among corn, cotton, and sorghum can reduce groundwater use while maintaining economically viable production. A county-level optimization framework is developed for 41 counties, incorporating crop-specific production characteristics and stochastic crop prices. The analysis compares profit-maximizing (PMAX) land allocations with water-minimizing (WMIN) allocations subject to alternative expected-profit tolerances and estimates the economic cost of additional groundwater conservation using the Groundwater Abatement Price (GAP).

The empirical results show that substantial groundwater savings can be achieved through profit-oriented crop reallocation. Regional irrigation water use declines from approximately 2.27 million acre-feet under the baseline allocation to 1.78 million acre-feet under PMAX, representing a reduction of approximately 497,783 acre-feet, or 21.90%. This reallocation is also highly profitable in its own right: expected regional profit rises from $275.50 million under the baseline to $1,081.74 million under PMAX, an increase of $806.24 million driven by the shift toward sorghum-dominant cropping. At the 5% expected-profit tolerance, WMIN reduces irrigation water use to approximately 1.77 million acre-feet, equivalent to a 22.03% reduction relative to baseline. The additional groundwater saving from moving from PMAX to WMIN, however, is only 2,903 acre-feet. This indicates that most of the groundwater-conservation potential identified through crop reallocation is already captured by the profit-maximizing allocation. Relaxing the tolerance further to 10%, however, yields a substantially larger additional saving of about 15,149 acre-feet, though at a much higher expected-profit sacrifice of approximately $41.20 million—indicating sharply diminishing returns as the region moves beyond the handful of counties where conservation is cheapest.

The county-level results further show a high degree of agreement between the two optimization objectives. PMAX and WMIN select the same land-allocation strategy in 38 of the 41 counties, while different allocations are selected only in Randall, Roberts, and Donley counties. In these three counties, additional groundwater conservation is achieved by shifting land away from corn and toward sorghum. Roberts records the largest percentage reduction in irrigation water use at 14.47%, while Donley provides the largest absolute additional saving at approximately 1,146 acre-feet. These results indicate that the remaining opportunity for groundwater conservation beyond the PMAX allocation is spatially concentrated rather than widespread across the region.

The economic trade-offs associated with these additional savings also vary across counties. The estimated GAP ranges from $73.73 per acre-foot in Randall to $112.39 per acre-foot in Donley, with Roberts recording a GAP of $87.22 per acre-foot. Across the three counties, approximately 2,903 acre-feet of additional groundwater can be conserved at a total expected-profit sacrifice of about $272,041, corresponding to a regional weighted GAP of approximately $93.70 per acre-foot. The variation in these values demonstrates that the economic cost of obtaining additional groundwater conservation depends on local production conditions and the crop reallocations available within each county.

Overall, the findings show that groundwater conservation and agricultural profitability need not be competing objectives across much of the Texas High Plains. Strategic crop reallocation can generate substantial reductions in irrigation water use while remaining consistent with profit-oriented production decisions. At the same time, the limited additional savings obtained under WMIN at the 5% expected-profit tolerance suggest that crop switching alone may provide relatively little additional conservation once economically preferred allocations have been adopted. The county-level variation in GAP further indicates that conservation policies should account for differences in the economic cost of water savings rather than applying a uniform approach across the region.

The framework provides a transparent basis for identifying where crop reallocation can contribute to groundwater conservation and where additional conservation involves greater economic sacrifice. Future research could extend the analysis by incorporating dynamic aquifer responses, technological adaptation, a broader set of crops, and uncertainty in crop yields as well as prices. Linking land-allocation decisions directly to changes in groundwater stocks would also provide additional insight into the long-run economic and hydrologic consequences of alternative conservation strategies. Such extensions would strengthen the assessment of how crop choice and land allocation can contribute to the long-term sustainability of irrigated agriculture in the Texas High Plains.

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Appendix

This appendix reports supporting diagnostics for the data construction and Monte Carlo price simulation described above. County-level results for all 41 counties, and the full 66-strategy feasibility screen, are available as supplementary material upon request.

Table A1: Data Quality Summary

Measure	**Value**
Counties	41
Years	23
County-year observations	943
Sorghum zero/nonpositive/missing yields	359
Cotton zero/nonpositive/missing yields	296
Corn zero/nonpositive/missing yields	541
Sorghum valid irrigation-intensity observations	839
Cotton valid irrigation-intensity observations	859
Corn valid irrigation-intensity observations	762

Note: The analysis contains 41 counties observed over 23 years (2000–2022).

Table A2: Price Simulation Diagnostics

	Sorghum	Cotton	Corn
Simulated mean ($/unit)	13.673	0.679	4.839
Simulated SD ($/unit)	3.147	0.108	1.346

Price correlation matrices

Historical (2013–2022)	Sorghum	Cotton	Corn
Sorghum	1.000	0.822	0.918
Cotton	0.822	1.000	0.870
Corn	0.918	0.870	1.000

Simulated (10,000 draws)	Sorghum	Cotton	Corn
Sorghum	1.000	0.701	0.739
Cotton	0.701	1.000	0.693
Corn	0.739	0.693	1.000

Note: Historical correlations are based on the 2013–2022 price window; simulated correlations are computed from 10,000 Monte Carlo price draws. Simulated correlations attenuate somewhat toward independence relative to the historical series because crop-specific kernel noise is added independently around each sampled historical year.

Table A3: Monte Carlo Convergence of Simulated Crop-Price Means

Draws	Sorghum mean	Cotton mean	Corn mean
1,000	13.740	0.679	4.850
2,500	13.693	0.680	4.875
5,000	13.635	0.678	4.829
7,500	13.653	0.678	4.835
10,000	13.673	0.679	4.839

Note: The stability of simulated price means as the number of draws increases provides a convergence diagnostic for the 10,000-draw specification used throughout the analysis.

Table A4: WMIN Strategy Frequencies across Expected-Profit Tolerances

ε	**Strategy**	**Composition**	**Sorghum (%)**	**Cotton (%)**	**Counties**
0.00	Strategy_57	Sorghum only	100	0	35
0.00	Strategy_1	Cotton only	0	100	1
0.00	Strategy_38	Sorghum–cotton	80	20	1
0.00	Strategy_63	Sorghum–corn	70	0	1
0.00	Strategy_65	Sorghum–corn	60	0	1
0.00	Strategy_66	Sorghum–corn	50	0	1
0.00	Strategy_8	Sorghum–cotton	30	70	1
0.05	Strategy_57	Sorghum only	100	0	36
0.05	Strategy_61	Sorghum–corn	80	0	2
0.05	Strategy_1	Cotton only	0	100	1
0.05	Strategy_38	Sorghum–cotton	80	20	1
0.05	Strategy_8	Sorghum–cotton	30	70	1
0.10	Strategy_57	Sorghum only	100	0	31
0.10	Strategy_47	Sorghum–cotton	90	10	7
0.10	Strategy_1	Cotton only	0	100	1
0.10	Strategy_40	Sorghum–cotton–corn	70	20	1
0.10	Strategy_8	Sorghum–cotton	30	70	1

Note: Frequencies sum to 41 counties within each ε level. Corn shares are the residual (100% minus sorghum and cotton shares) and are omitted from the table for space; Strategy_40 allocates the remaining 10% to corn.